Groningen data driven subsidence forecast – addressing aquifer depletion uncertainty in a Bayesian framework

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Abstract

After the discovery of the Groningen gas field in 1959, land subsidence due to gas production was recognized as a potential threat to water management in the Province of Groningen. During the 60 years of gas production from the field, the cemented reservoir sandstone has compacted with tens of centimetres due to the decrease of the pressure. The resulting land subsidence has been monitored frequently over the past 60 years by geodetic measurements (optical levelling, InSAR, GNSS). In this study, subsidence models were calibrated using a Bayesian Monte Carlo-Markov chain approach. Subsidence forecasts are based on the short-term production scenarios, the long-term pressure equilibration phase in the gas field and connected lateral aquifers.

Introduction

The Groningen gas field is the largest gas field in Europe with a gas volume of around 2900 billion cubic meters (De Jager and Visser, 2017). A large part of the Groningen province lies below the sea level, an area that requires active water management. Significant compaction and subsidence due to gas production can be regarded as a threat to constant groundwater levels with possible consequences for land usage and infrastructure like dikes and bridges. Large additional subsidence volumes require additional efforts from water boards to preserve the usage of the land as it is today.

This subsidence threat has long been recognised, which resulted in many studies (e.g., van Thienen-Visser and Fokker, 2017 and van Eijs and van der Wal, 2017). These studies all had the objective to match a geomechanical model to the available geodetic data. Subsequently, the history matched model is then used for forecasting the future subsidence.

Besides the impact on groundwater levels, reservoir compaction has also been correlated to the occurrence of induced seismicity (Bourne et al. 2014). Although induced seismicity is mainly caused by poro-elastic effective stress changes, it is observed that the highest frequencies and magnitudes of earthquakes occur in areas where the compaction is highest. Because of the seismic activity, the minister of Economic Affairs and Climate Policy decided to end the production from the Groningen field in 2022. This decision will stop further depletion of the main reservoir layer and hence subsidence of the field at large. However, it does not imply that further compaction and subsidence will cease immediately. Both visco-plastic compaction and pressure redistribution will lead to moderate amounts of further subsidence above the gas field. Another potential source for further compaction is the pressure decline in the aquifers that are laterally connected to the gas field. Because there are no wells in these aquifers, the pressure cannot be measured directly and can only be estimated from calibration and/or inversion of the geodetic data.

Methods

There are multiple possibilities to calibrate a model to measured data. In the past, deterministic models were manually fitted to the data. These methods are prone for non-uniqueness and often lack a proper quantification of the uncertainty. A stochastic approach would circumvent these drawbacks where data is used to find both the optimal match and its uncertainty. In this study, analytical and therefore fast models are used in the statistical methodology for matching and forecasting the subsidence above the Groningen field. This method is described in detail by Bierman and Towe (2020). The method distinguishes the model uncertainty (Σ_{emp}) and geodetic measurements uncertainty (Σ_{geod}) that in total provide a description of the prediction interval. The probability is based on the goodness of fit expressed by the value for the negative log-likelihood (NLL).

Furthermore, the workflow is designed to address the following additional questions:

- Can we find properties, based on well or seismic data, that correlate to rock mechanical data to create prior spatial compressibility maps?
- What is the most likely aquifer realization using the geodetic data?
- How improve the spatial and temporal match with the geodetic data?

To obtain the answers to these questions, the following workflow was constructed (Figure 1). A description of the steps, including the results for each step is presented in the next sections.

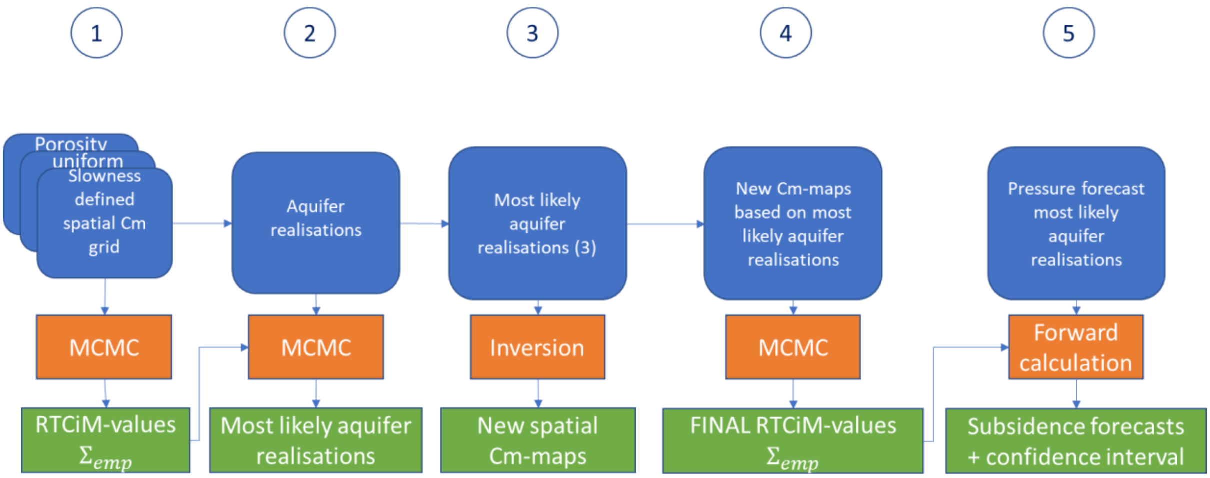

Figure 1 Scheme of the 5-step workflow. Input of each step in blue, the orange boxes visualize the calculation method and in green, the results per step.

Step 1: Generation of the prior rock compressibility grids and calculate a first set of compaction model and uncertainty parameters:

The following correlations were used as a prior input in the calculations: Cm – porosity, Cm – slowness (1/sonic velocity) and a uniform Cm (uniaxial compressibility) grid for the area above the gas field. The porosity, derived from core and logs, and the sonic slowness, derived from seismic data, are used to build spatial maps for the Cm values that are used in the Rate Type Compaction Model (De Waal and Smits, 1988, Pruiksma et al., 2015). This compaction model allows for a description of stress rate dependent compaction. In short, the model describes a first direct strain response, ε_d, to a change of the loading rate (e.g. caused by the gas production), followed by a more gradual response referred to as the secular strain, ε_s. The total strain is defined as the sum of a direct part and a time dependent secular part:

$\varepsilon = \varepsilon_d + \varepsilon_s$. More details of the implementation of the RTCiM, where the i stands for an isotachen formulation, can be found in NAM (2020).

For these spatial maps the most likely RTCiM parameters and uncertainty parameters are found using a Monte Carlo-Markov Chain (MCMC) method. This inversion procedure uses the geodetic data and converges to a compaction scenario with the lowest value for the negative log likelihood and calculates the value for the model uncertainty (Σ_{emp}). Knowing the thickness and the pressure, the most likely RTCiM parameter values can be calculated. In step 1, only geodetic benchmarks above the gas field are used in the calibration, because of the well constrained pressure input in the workflow coming from the Groningen reservoir model.

Step 2, selection of the aquifer realisations

Using the obtained results for the uncertainty (Σ_{emp}) and RTCiM parameters from step 1, the objective of step 2 is to test the aquifer realisations in combination with the spatial Cm grids. To test multiple aquifer scenarios in the southwestern aquifer, box-models that allow for multiple pressure profiles per box over the length of the box, were created. Box-models are defined by fault structures (long edges of the box) and the boundaries of the gas fields at the western short edges of the boxes. The boundaries of the boxes are controlled by the gas pressures in the Groningen field and the pressures of the smaller gas fields to the west of Groningen. Combining the defined box-models and legacy reservoir models, 3126 possible aquifer realisations for each prior compressibility grid, are tested to obtain a value for the NLL. The computational effort is relatively small because of the fixed values for the model uncertainty (Σ_{emp}) and RTCiM parameters from step 1 that are assigned to both the gas field and aquifer reservoir rock properties. The geodetic benchmarks above the aquifers are used to assess the modelled subsidence fit to the measurements. The most likely realisation, defined by the NLL, for each of the possible spatial Cm grids is selected, resulting in three modelled subsidence scenarios.

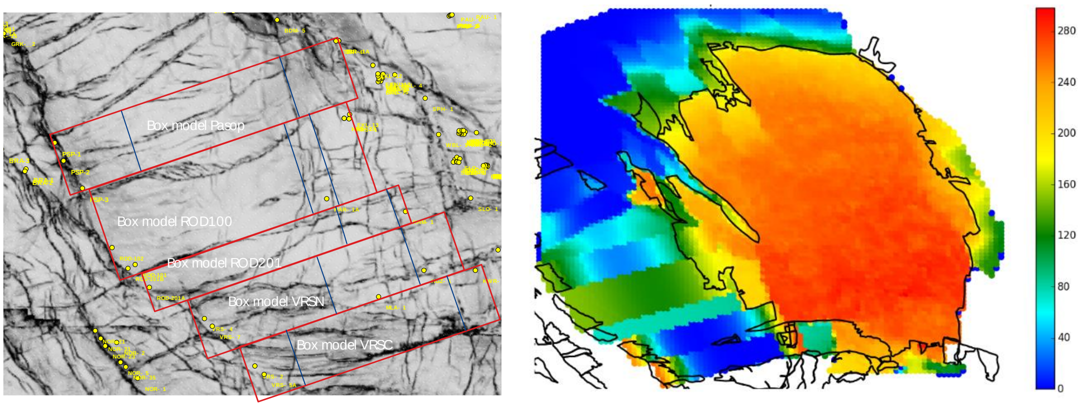

Figure 2   left: box models in the southwestern aquifer. Right: an example of a pressure depletion realization that shows the boundaries of the box-models as well in the southwestern part of the figure.

Step 3, inversion to obtain optimal spatial Cm grids

To reduce local higher residuals in the three subsidence scenarios, step 3 uses an inversion scheme to give more weight to the measurements in these areas. Rather than using a smoothing parameter, the spatial Cm maps of step 1 are used as a prior input into the inversion scheme where the weight of the prior is set by a penalty factor. A trade-off between the goodness of fit, provided by the negative log likelihood and the outcome of a geologically reasonable distribution, guided by the prior spatial map, concluded the value of the penalty factor. Step 3 results in 3 new spatial compressibility maps for each of the three subsidence scenarios shown in Figure 3.

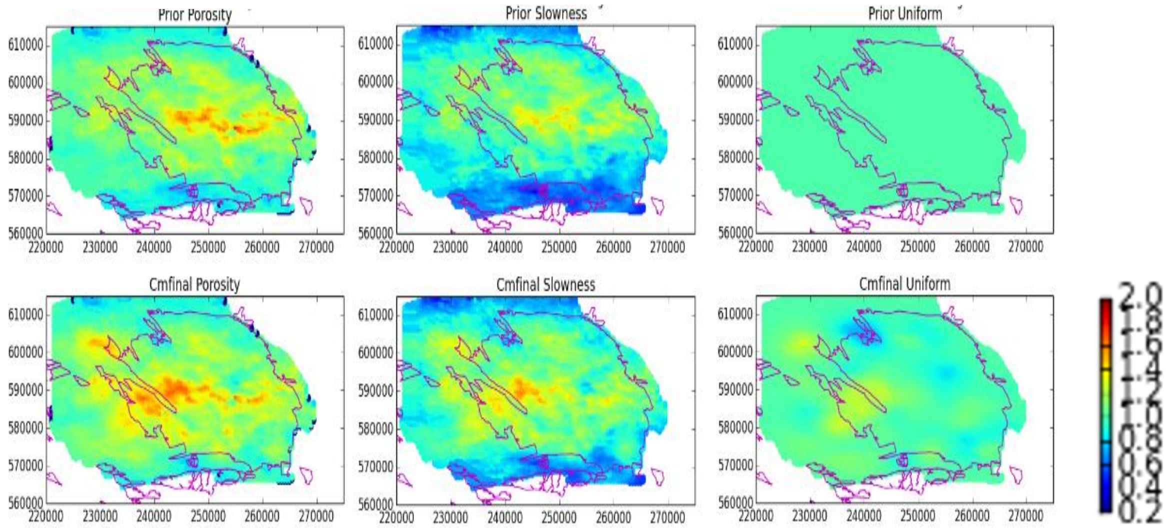

Figure 3   Results for the spatial Cm inversion using a value for the penalty factor of 5. The columns indicate the prior Cm grid. The top row shows the prior Cm grids and the bottom row the resulting spatial Cm grids.

Step 4, improve the temporal fit to the data, by adjusting the RTCiM parameter values

In step 3, local spatial mismatches are decreased. In step 4 the match to the temporal signal from the measurements is improved including a new assessment of the Σ_{emp}. New values for the RTCiM parameters are derived after the application of the MCMC statistical workflow and using the new spatial Cm maps from step 3. This step resulted in adjusted posterior values for the RTCiM parameters and the parameter values that describe the Σ_{emp}. Figure 4 shows a coverage plot for the most likely subsidence scenario. The blue vertical lines in the left graph show the bandwidths of the predicted displacements. The red points in the same graph show the measured displacements. The horizontal axis is defined by the rank of the median predicted displacements (more than 10000 data points). With a perfect model, the coverage would be 95%, implying that 95 % of the measurements fall into their respective prediction intervals. The result after step 4 is close to this value (92%), a value that improved when compared to the results after running step 1. More important is the improvement of the coverage per benchmark (map on the right in Figure 4). No local or regional clusters of benchmarks with a poorer coverage are observed. The adjusted Cm grid in step 3 contributed most to this improvement.

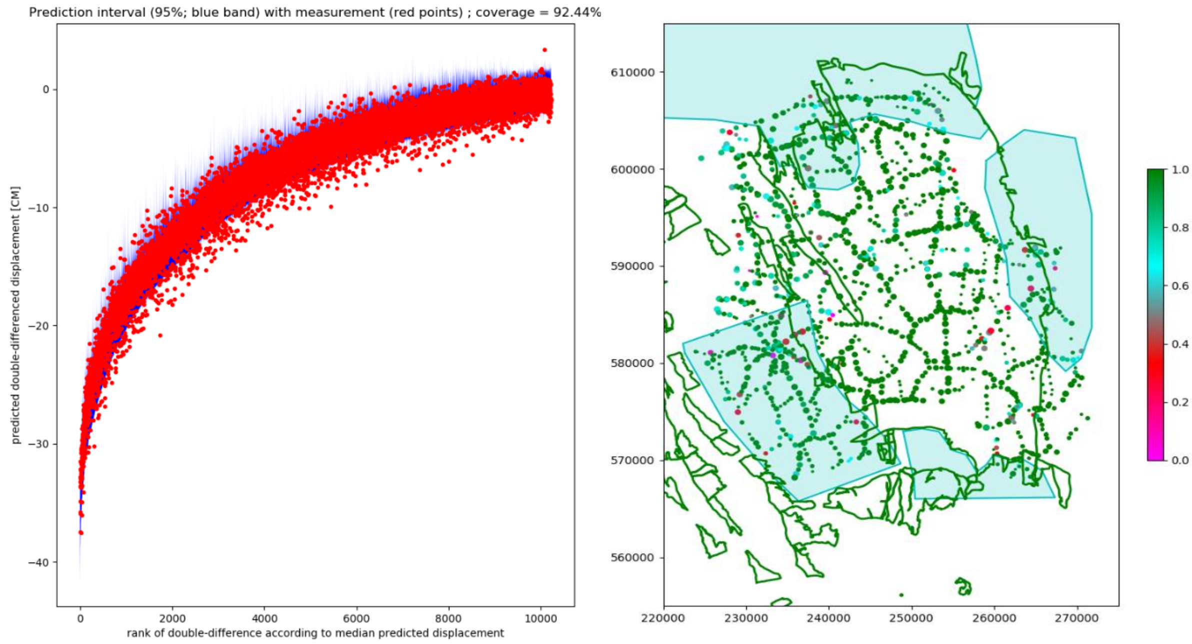

Figure 4 Prediction interval and coverage (left graph). Right picture: coverage per benchmark. The size of the dot indicates the number of measurements that are linked to the benchmark. The colour indicates the fraction of measurements that are inside the prediction interval. Dark green means that all measurements in time linked to the specific benchmark are inside the prediction interval.

Step 5, subsidence forecasts

Step 5 executes the forward calculation to obtain the forecast for the most likely subsidence scenario including its uncertainty. The estimated parameters for the Σ_{emp} provide the uncertainty of the forecast, i.e. the confidence interval. Figure 5 shows for five locations above the field the model results with the historical data and the subsidence forecast, including a 95% confidence interval of the model.

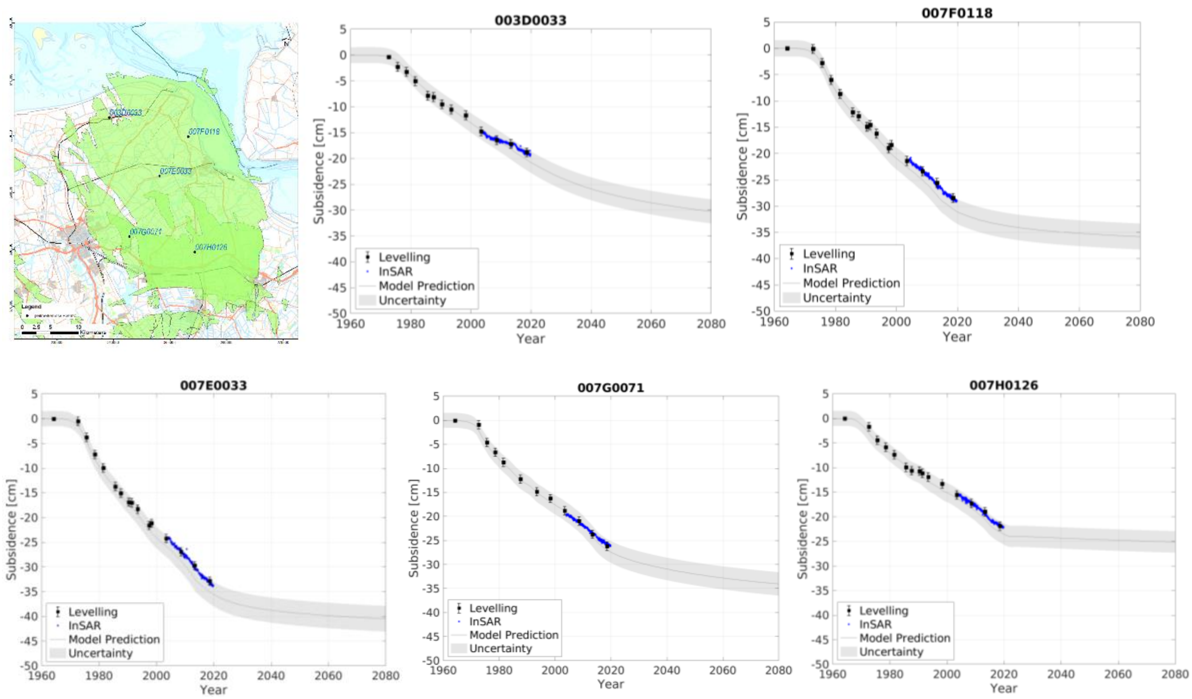

Figure 5 Subsidence at benchmark locations till 2080: dark grey line is the predicted subsidence, grey is the P95 confidence interval, black squares are levelling measurements plus uncertainty, the blue dots are the InSAR measurements.

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